Decision Support Model for Monitoring Psychophysiological State with Wearable Edge AI

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Abstract

In the modern world of operations that include defense, emergency medicine, and control of energy systems, the most unpredictable element remains human beings. Machines can be tested and software can be debugged, but the human factor shifts rapidly. A person may begin the day sharp and fully concentrated and then in just a few hours lose focus, slow down reactions, and make mistakes. Some of these mistakes are small and only add noise to the workflow, but others can have fatal consequences.

Traditional methods of monitoring stress and readiness are insufficient. Questionnaires rely on subjective answers. Medical check-ups are periodic and static. Psychological interviews capture a snapshot but not the constant dynamics. This means that real changes often pass unnoticed until the damage is already visible.

This work describes a wearable system with Edge AI that addresses the gap. The system combines two measures. The first is the Cognitive Readiness Index or CRI, which reflects short-term readiness. The second is the Destabilization Risk Index or DRI, which reflects long-term resilience. Both rely mainly on HRV data, supported by electrodermal activity, motion signals, and body temperature. Computation is done locally on the device. The aim is to reduce immediate errors and at the same time protect long-term health.

Keywords: FPGA, Edge AI, Zynq SoC, Psychophysiological Monitoring, Decision Support Systems, HRV, Acute Stress Detection, Wearable Technology.

1. Introduction.

The decline of performance under pressure is well documented. At first it shows in hesitation and slightly slower responses. Later the same pressure leads to poor concentration and higher error rates. After extended exposure it becomes clear fatigue or even full breakdown.

Examples are easy to find. Soldiers on extended field exercises lose attention after several nights without proper sleep. Doctors in emergency departments start the day performing at a high level but after twenty hours on duty they show lapses and misjudgments. Operators in power grid control rooms maintain concentration for hours but after too many alarms their attention drifts and serious mistakes may follow up with [1].

Existing systems are not sufficient. Self-assessment forms are unreliable because people misjudge themselves. Medical evaluations are too rare to be useful in dynamic environments. Stress is continuous and fast while evaluation tools are static and slow.

The technology of wearables has opened a new possibility. Small sensors for ECG, accelerometers, and skin conductance can be worn without interfering with tasks. Edge processors can analyze the data directly on the device. This solves two major problems. First, it works without internet, which is important for secure and remote zones. Second, private health data remain local, which protects users from surveillance risks.

Most current solutions look only at short-term acute stress or only at long-term chronic effects. Real life is both. Short stress events accumulate and create chronic risk. That is why the proposed model integrates both.

2. Methodology.

Hardware platform

The system is a wearable medical diagnostic complex built on FPGA Zynq. The choice is motivated by three reasons. First, FPGA supports parallel data processing, which is needed for real-time signals. Second, energy use is low, which is important for field work. Third, FPGA allows integration of AI accelerators on the same platform.

The sensors included are ECG for HRV measurement, electrodermal activity sensors for arousal, IMU for physical activity and posture, and temperature sensors for long-term physiological tracking. An accelerator runs neural networks directly on the device so only indices are stored or sent.

Data Acquisition and Feature Extraction

The R–R interval is the time between two consecutive R-peaks in the QRS complex of an electrocardiogram (ECG). It reflects the duration of one cardiac cycle and is the fundamental measure used to calculate heart rate variability (HRV). The analysis is centered on Heart Rate Variability (HRV), a widely accepted marker of autonomic nervous system (ANS) dynamics [2,3]. From ECG signals, R–R intervals are extracted. For each time window, a feature vector is formed, including time-domain features, frequency-domain features, nonlinear features [4].

One important metric is RMSSD, which reflects vagal activity:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2},$$

where N is the number of R–R intervals in the window.

RMSSD reflects short-term variability. Low RMSSD is usually a sign of stress or fatigue.

Other metrics include SDNN, LF/HF ratio, and nonlinear measures such as entropy. Each metric gives only partial information. Together they produce a more stable view of autonomic balance [5].

Context awareness and adaptive baselines

Physiological signals cannot be interpreted without context. A high heart rate may signal stress but it may also mean that the person is running or climbing stairs. To reduce false alarms, IMU data are added to interpret changes correctly.

Baselines are not constant. Normal values for a soldier in the first week of training are not the same as after a month. To capture gradual adaptation, the system uses Exponentially Weighted Moving Average:

$$\mu_t = \alpha x_t + (1-\alpha)\mu_{t-1},$$

where α is the smoothing factor, x_t is the latest observation, and μ_t is the updated mean.

This approach updates baselines smoothly. Temporary spikes do not change the baseline but long-term shifts are reflected.

Cognitive Readiness Index (CRI)

The Cognitive Readiness Index is a measure of immediate readiness. The model calculates Mahalanobis distance between current features and baseline:

$$D^2 = (x-\mu)^T\Sigma^{-1}(x-\mu),$$

where x is the feature vector, μ is the baseline mean, and Σ is the covariance matrix.

This distance is then transformed into a score:

$$CRI = e^{-\beta D^2},$$

where β is a scaling parameter.

High CRI means the person is close to baseline and ready. Low CRI means deviation and risk.

To link CRI with real errors, logistic regression is applied:

$$P(E) = \frac{1}{1+e^{-(\gamma_0+\gamma_1 CRI)}},$$

where $P(E)$ is the probability of error, and γ_0, γ_1 are regression coefficients.

This equation estimates the probability of mistakes. Tests have shown that lower CRI correlates with higher error rates in vigilance tasks.

Destabilization Risk Index (DRI)

The Destabilization Risk Index reflects long-term resilience. It is based on a CNN LSTM neural model trained on sequences of HRV and related features. CNN layers extract local patterns. LSTM layers capture temporal dynamics.

To create a composite index, the neural model's output is combined with anomaly scores and historical data using a weighted scheme:

$$DRI = w_1 P_{CNN-LSTM} + w_2 S_{anom} + w_3 H_{hist}, \sum_{i=1}^{3} w_i = 1\,,$$

where $P_{CNN-LSTM}$ is the probability of being in a pre-episode state, S_{anom} is the anomaly score, and H_{hist} represents historical destabilization factors.

3. Results

At the current stage results are expected rather than final. Cognitive Readiness Index is predicted to show correlation with errors and reaction times in laboratory tests. Adding IMU context should reduce false alarms. Destabilization Risk Index is expected to achieve AUC higher than 0.85 in detecting early destabilization [7]. A prototype on FPGA Zynq will be prepared and will be tested first with soldiers in training environments and later in emergency response drills.

Comparisons will also be done against classical surveys and medical instruments to see whether the device produces equal or better prediction.

4. Discussion

The main contribution is integration of short-term and long-term monitoring. Most previous systems separate them. The theory of allostatic load describes how repeated stress leads to chronic burden [8]. The combined model is an attempt to reflect this.

Cognitive Readiness Index is tactical. It helps leaders know who is ready at the moment. Destabilization Risk Index is strategic [9,10]. It provides early warning before a breakdown. Together they give a more complete picture of human performance.

Local processing on the device has several benefits. It ensures privacy because raw data are not transmitted [11,12]. It ensures independence because no internet is required. Both are critical in secure and remote conditions.

Challenges remain. Collecting long-term datasets is difficult. Deep learning models require large training data. Adoption may face resistance because people fear surveillance. To solve this, clear rules and transparent governance must be developed. Trust is essential. Without trust the system will not be accepted.

5. Conclusion

This work presented a model for monitoring psychophysiological state with a wearable Edge AI device. It combines Cognitive Readiness Index for short-term readiness with Destabilization Risk Index for long-term resilience. Both indices are based on HRV supported by other signals. Baselines are adaptive. Context is included. Computation is local.

Future work includes collection of larger datasets, validation in real field conditions, and development of transparent policies. If implemented with trust, the system could reduce immediate mistakes and protect long-term health [13].

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